



A Deep Learning Approach to the Transformer Life Prediction Considering Diverse Aging Factors

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The reliability of a high-capacity power transformer is fundamental to the stable operation of power systems. However, characterization of the transformer aging process is a difficult task, considering the diverse aging factors in its life cycle. This prevents effective management of such equipment. In the work, we study the aging phenomenon of power system transformers, whose representative degeneration variables are extracted from real transformer operational data. Combining with the average life of the equipment, the extracted features are used as indicators for the transformer reliability evaluations. We developed a deep learning-based approach using a convolutional neural network for effective equipment life prediction. The performance of the transformer life prediction model is verified using field-test data, which demonstrates the superior accuracy of the presented approach.

Keywords: Transformer, life differentiation phenomenon, life prediction, convolutional neural network, aging factors

INTRODUCTION

The model power system quickly evolved with the accelerated marketization incentives. In this process, the safety and reliability of the power system became important concerns to be addressed. With the narrower profit margin, the system operators face multiple challenges: ensuring safety, reducing electricity prices, and increasing efficiency. In recent years, the system operator of China, State Grid, has found a relatively low age among scrapped samples and a relatively high proportion of over-aged samples among the transformer equipment. The problems are as follows: First, the scrapping age of substation equipment is usually 6–10 years, and the average service life of main equipment is lower than the transformer depreciation period and the pricing depreciation period. To a certain extent, this will result in a waste of depreciation costs. It is difficult to fully incorporate into the cost of transmission and distribution prices. Second, the over-aged transformers have accounted for 10% of the original value of the physical assets of the power grid. Some of the over-aged transformers can still operate normally. Under strict supervision and examination requirements, the over-aged transformers cannot be depreciated, which reduces the electricity price level and the company's investment capacity.

Reliability is an important indicator for verifying the safe operation of equipment (Song and Cheng, 2015). It refers to the ability or possibility of equipment to perform specified functions without failure within a certain period and under certain conditions (Song, 2001). Overall, the operating life of primary equipment in the power grid is significantly different, and this difference increases the difficulty of primary equipment reliability assessment and reasonable life estimation. Particularly in the field of reasonable life prediction of transformers, this difference in phenomena is rarely studied in current research.

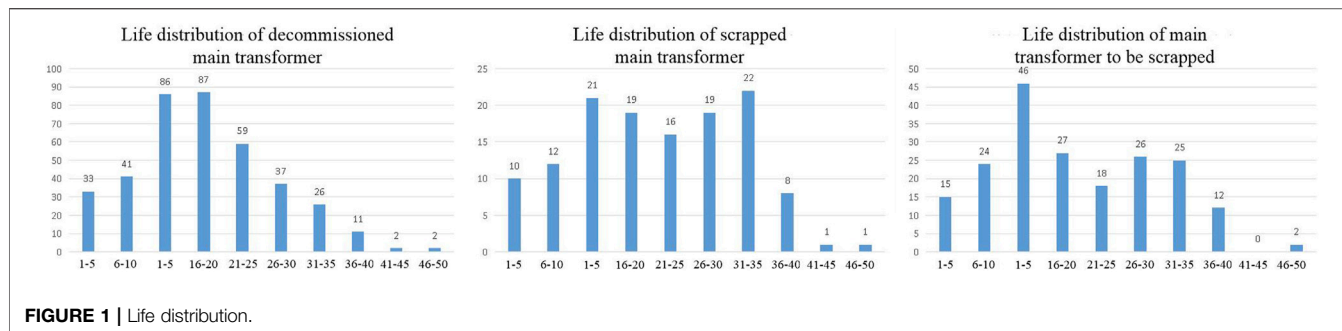


FIGURE 1 | Life distribution.

Transformers are the current representative of large-power equipment, which include multiple failure forms such as discharge, overheating, or both (Castro and Miranda, 2005; Jongen et al., 2007; Zheng et al., 2012; Fox et al., 2019). The reasonable life estimation of the transformer also belongs to the category of fault prediction. The main method is to predict the possible future failures through the historical data obtained by monitoring and to ascertain the remaining life. At present, transformer life prediction models can be divided into physical failure mechanism models and data-driven models (Abu-Elanien and Salama, 2012; Zhou, 2013; Ignacio et al., 2018; Zhang et al., 2018). The physical failure mechanism model is based on the transformer failure mechanism and mathematically characterizes the material failure process. Chen and Liu (2020) proposed a transformer life prediction model based on the hidden Markov model. Shi et al. (2020) established the Arrhenius equation based on the degradation mechanism of variable activation energy and then predicted the remaining life of the transformer. Based on the data-driven life model, the operating parameters that can characterize the degree of transformer degradation are obtained mainly based on the monitoring technology, and the operating trend of the parameters is directly predicted (Hu et al., 2022). Common operating parameters include vibration signal, noise signal, and insulating oil content (Bacha et al., 2012; Ma et al., 2013; Tian et al., 2013; Guo et al., 2017; Yan et al., 2020). This method does not involve a specific failure mechanism, so it has a wider scope including the long-short-term memory network-based life prediction model (Dai et al., 2021), the life prediction model based on the SVM algorithm with RBF as the kernel function, etc. (Wang, 2021).

However, both the physical failure mechanism model and the data-driven model are based on the specific operating conditions of the transformer, that is, monitoring the parameter distribution of the equipment in the time series and space series and predicting the life through the model (Ishak, 2010; Husnayain et al., 2016; Qian et al., 2018). However, the model established based on the aforementioned method has some limitations because the parameters are derived from a single device, so the application object is also limited to a specific type of device. State Grid’s transformers have the characteristics of a large number of equipments, wide distribution, and complex sources. It is difficult to use traditional methods to evaluate the life of all equipment.

TABLE 1 | Corresponding parameters of equipment with rated capacity.

Rated capacity	α	β	E	x_h	x_l
1	36.15	4.324	32.91	40%	40%
1.6	18.73	1.995	16.60	0	17%
1.8	29.64	4.504	27.05	0	0
2	22.56	2.218	19.98	0	0
2.5	25.94	2.516	23.02	15%	0

Based on a convolutional neural network, this article proposes a transformer life prediction method considering the difference in transformer life. First, according to the factory information and scrap age information of scrapped transformers provided by a company, four types of data of rated capacity, voltage level, manufacturer, and workplace are screened out. The characteristics of its life distribution are analyzed, respectively, and data of average life, life concentration, and the proportion of high-life equipment and low-life equipment were obtained. The aforementioned total of 16 data were taken as input, and the transformer age was taken as output. The convolutional neural network was trained to obtain the life prediction model. Compared with the traditional life prediction model, the advantages of the model proposed in this article are 1) considering the influence of the life difference phenomenon on the reliability of the transformer, the prediction accuracy is improved; 2) since the input is the equipment delivery and operation information and does not involve the specific operation conditions, the life prediction can be carried out before operation, and the operation and maintenance strategy can be formulated as soon as possible according to the prediction results.

LIFE DIFFERENCE PHENOMENON

Statistical statistics are carried out on the decommissioned, scrapped, and to-be-scrapped transformers of a power supply company, and a statistical graph is drawn, as shown in Figure 1. It can be found that the life distribution of the transformer is close to the normal distribution. Most of the equipment life is in the middle interval, and there are few high-life equipment and low-life equipment. However, this phenomenon increases the difficulty of equipment operation and maintenance. For possible low-life equipment, it should be the focus of attention

TABLE 2 | Corresponding parameters of equipment at each voltage level.

Voltage level	α	β	E	x_h	x_l
6kV	31.68	2.516	28.11	29%	12%
10kV	20.75	2.116	18.38	3%	24%
35kV	23.46	2.598	20.84	6%	19%
110kV	26.15	3.428	23.50	4%	14%
220kV	35.18	3.245	31.53	33%	0

TABLE 3 | Corresponding parameters of equipment of each manufacturer.

	α	β	E	x_h	x_l
A company	13.94	5.457	12.86	0	33%
B company	25.45	1.807	22.63	25%	0
C company	28.73	4.241	26.13	7%	7%
D company	27.83	4.59	25.43	0	0
E company	27.13	2.668	24.12	17%	0

TABLE 4 | Corresponding parameters of equipment of all affiliated companies.

	α	β	E	x_h	x_l
A power supply company	18.84	1.817	16.75	3%	31%
B power supply company	19.02	1.799	16.91	5%	21%
C power supply company	25.38	2.099	22.48	0	17%
D power supply company	19.84	1.921	17.60	6%	29%
E power supply company	15.71	1.518	14.16	0	31%

and is necessary to increase the frequency of maintenance, timely maintenance, and improve equipment reliability. For possible long-life equipment, appropriate attention can be reduced to save costs, analyzing the life distribution chart; dividing the equipment into older equipment, normal equipment, and younger equipment according to the distribution law of equipment life; and counting their proportions in the total equipment respectively; and summarizing the distribution law of equipment life. The equipment is divided into 5-year intervals. With the increase in service life, the service life in this interval increases first and then decreases; The pieces of equipment with a service life of 11–15 years are more than twice that of 6–10 years, and the increase is significantly greater than that in other ranges. The pieces of equipment with a service life of 36–40 years are less than 1/2 of that of 31–35 years, and the decrease is significantly greater than that in other intervals. Therefore, equipment with a service life of 10 years or less (main transformer and disconnecter) is defined as low-life equipment, equipment with a service life of 36 years or more is defined as high-life equipment, and other equipment is defined as normal equipment.

When the equipment is put into operation, it is necessary to evaluate the reliability of the equipment to facilitate the formulation of the operation and maintenance strategy. Due to the lack of operational data as the basis for evaluation, the equipment can only be roughly evaluated through historical data, such as manufacturer and operation city before the equipment is put into operation. Due to different production processes, equipment produced by different manufacturers will

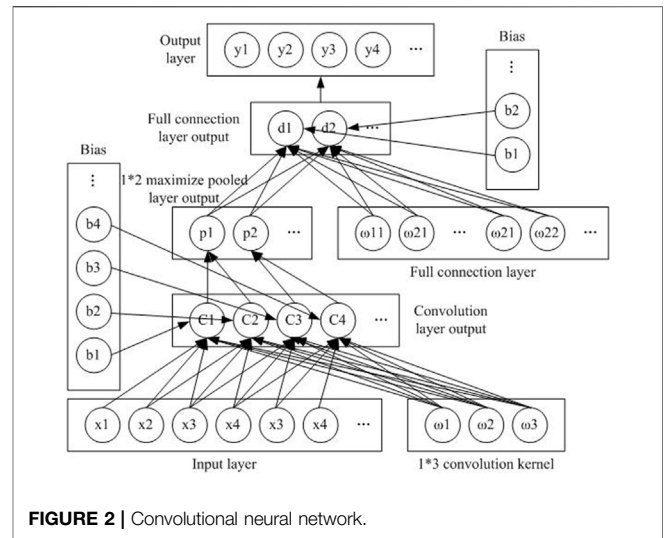


FIGURE 2 | Convolutional neural network.

also have different characteristics in reliability. Similarly, different operating cities will have different working environments, which will further affect the reliability of the equipment. The extraction of reliable data from this kind of text information is key to the reliable evaluation of equipment before operation.

EXTRACTION OF TRANSFORMER AGING FACTORS

In the transformer operation and maintenance data, the average life is the most intuitive embodiment of equipment reliability, and it is also important data that can be used for life prediction. However, the data on average life cannot reflect the impact of life differentiation. Therefore, it is necessary to extract the aging factors that can reflect the phenomenon of life differentiation from the transformer life distribution data to improve the accuracy of reasonable life prediction.

The life differentiation characteristics of equipment can be described by three parameters: life concentration, the proportion of high-life equipment, and low-life equipment. Life concentration indicates the concentration degree of transformer life distribution. The more the proportion of main transformers is close to the average life, the higher the life concentration. The proportion of high life and low life is the proportion of transformers with a life of more than 35 years and less than 10 years in the total number, which can be obtained directly through statistics.

Because the Weibull distribution can be used to describe the characteristics of equipment life distribution, life concentration and average life can be expressed by the relevant characteristics of the Weibull distribution (Zhou et al., 2013). The Weibull distribution was proposed by Swedish physicist W. Weibull in 1939. It is mainly used to describe the probability distribution of material fatigue strength. The Weibull distribution is widely used in reliability engineering, especially in the distribution form of cumulative wear failure of electromechanical products. Due to the

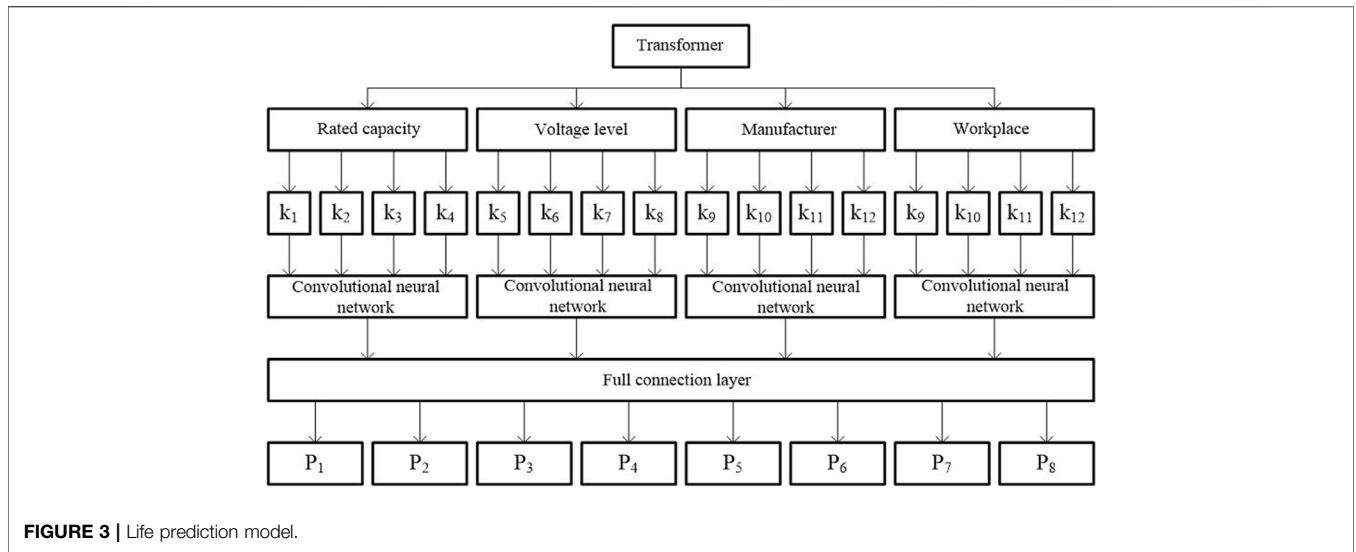


FIGURE 3 | Life prediction model.

TABLE 5 | Life prediction model parameters.

Network layer	Parameters	Parameters	Parameters	Parameters
Input layer	1*4	1*4	1*4	1*4
Convolution layer (Relu)	64-[1*2]	64-[1*2]	64-[1*2]	64-[1*2]
Convolution layer (Relu)	64-[1*2]	64-[1*2]	64-[1*2]	64-[1*2]
Convolution layer (Relu)	128-[1*2]	128-[1*2]	128-[1*2]	128-[1*2]
Flatten layer				
Full connection layer (Tanh)		128		
Full connection layer (Tanh)		128		
Classification layer (Softmax)		8		

ease of inferring the distribution parameters using the probability value, it is widely used in the data processing of various life tests. The probability density of the Weibull distribution is shown in Eq. (1).

$$f(t) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^\beta}, \quad (1)$$

where α is the scale parameter and β is the shape parameter. According to the properties of the Weibull distribution, the shape parameter β is related to the concentration of life distribution. The larger the β , the more concentrated the life distribution. The smaller the β , the more dispersed the life distribution. The average life of the equipment can be expressed by mathematical expectations. Therefore, the average life of the equipment can be calculated according to the parameters of the Weibull distribution and the service life expectation, as shown in Eq. (2).

$$E = \alpha \cdot \Gamma\left(1 + \frac{1}{\beta}\right). \quad (2)$$

The fitting method of the Weibull distribution characteristic parameters is as follows:

- 1) The service lives of n different equipment with the same feature were arranged from short to long, which are N_1, N_2, \dots, N_n , respectively;
- 2) Eq. (3) was used to calculate the unbiased estimation of fatigue cumulative distribution F ;

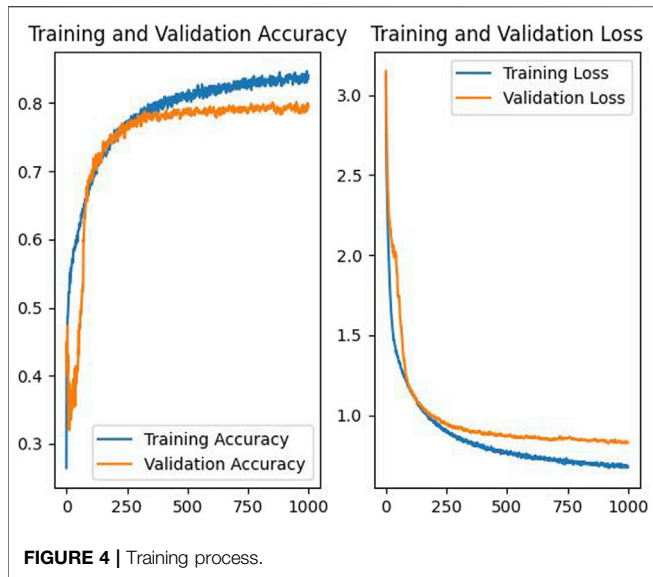
$$F = \frac{i-0.3}{n+0.4}. \quad (3)$$

- 3) Eq. (4) was fitted to obtain an unbiased estimation of α, β .

$$\ln(1 - F) = -\left(\frac{N}{\alpha}\right)^\beta. \quad (4)$$

Now, the reliability information such as the rated capacitance, voltage grade, manufacturer and affiliated company of the main transformer, and the corresponding proportional parameters are counted, respectively; scale parameter, α ; shape parameter, β ; the average life (mathematical expectation), E ; proportion of high-life equipment, x_h ; and proportion of low-life equipment, x_l are shown in Tables 1–4:

Next, according to the aforementioned data and combined with the life distribution of equipment, a reasonable life prediction model of transformers based on a convolutional neural network is established.



AI-BASED APPROACH TO THE LIFE PREDICTION MODEL

Convolutional Neural Network

In recent years, with the rapid development of the computer field, deep learning has been applied to all aspects. The convolutional neural network possesses a considerable ability for face recognition and image recognition and has great application prospects in the field of transformer fault diagnosis. In this article, a reasonable life prediction model of a transformer is constructed based on a convolutional neural network. A convolutional neural network generally includes an

input layer, convolution layer, pooling layer, full connection layer, and output layer (Zhou et al., 2017). Taking one-dimensional data as an example, its general structure is shown in **Figure 2**.

The input layer is the input data of some characteristic quantities, including rated capacity, voltage level, manufacturer, and workplace. These are transformed into digital features using the Weibull distribution as input, such as x_1, x_2, x_3 , as shown in **Figure 2**.

The convolution layer is equivalent to a feature-extraction process. The important features are extracted through the convolution kernel during the movement of the input layer, as shown in **Figure 2**. Taking the 1×3 convolution kernel as an example, the calculation process is as follows:

$$c_n = x_n \times \omega_1 + x_{n+1} \times \omega_2 + x_{n+2} \times \omega_3 + b_n, \quad (5)$$

where x is input, ω is the weight, and b is the offset. The calculated results can use Relu, Tanh, and other activation functions as the output of each neuron in the convolution layer, that is, $C_n = f(cn)$. The expression of the activation function is as follows:

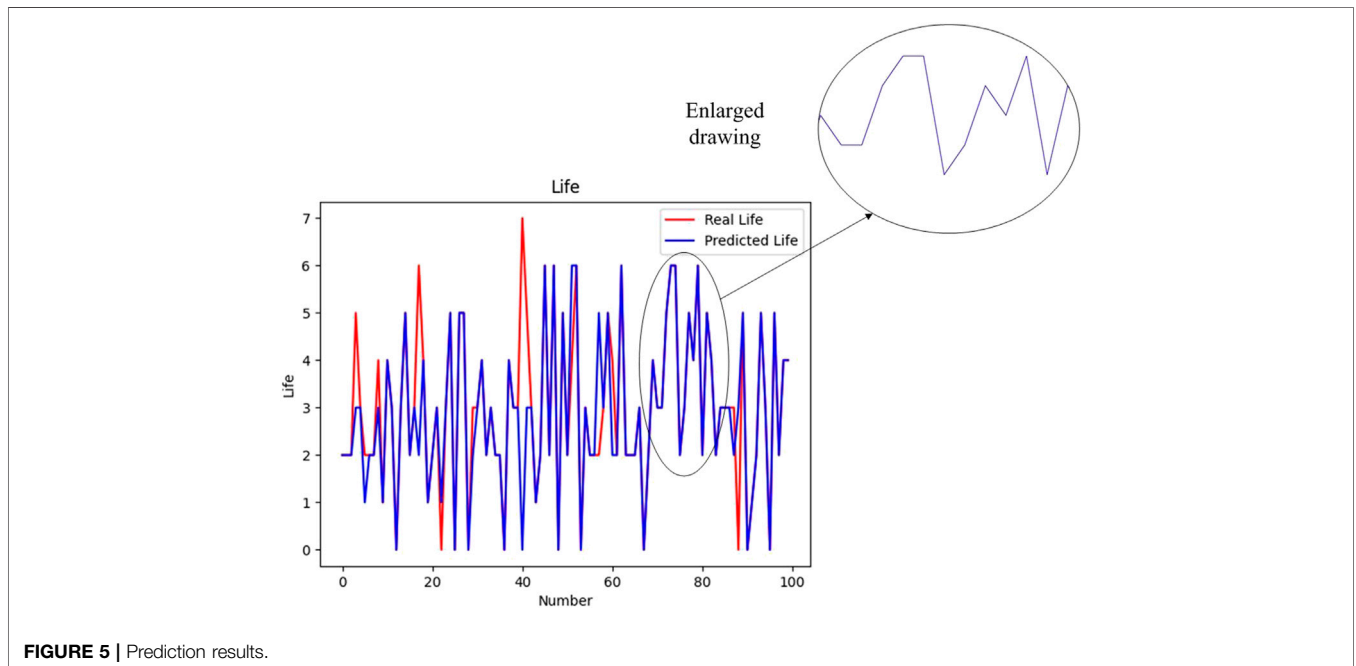
$$\text{Relu } f(x) = \max(0, x), \quad (6)$$

$$\text{Tanh } f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \quad (7)$$

The pooling layer mainly reduces the amount of calculation in the neural network, as shown in **Figure 2**. Taking the 1×2 maximum pooling layer as an example, the calculation process is as follows:

$$p_n = \max(C_n, C_{n+1}). \quad (8)$$

The full connection layer is the neural network, as shown in **Figure 2**. Its calculation steps are as follows:



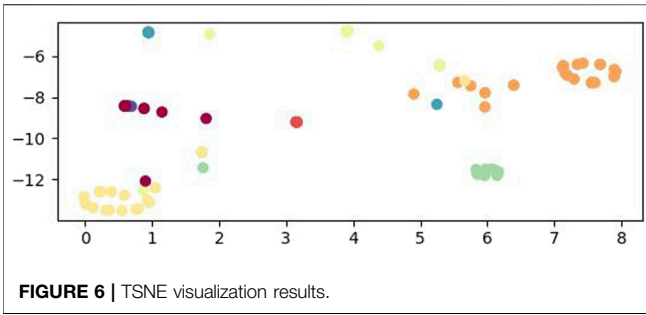


TABLE 6 | Comparison of different life prediction models.

Life prediction model	Accuracy (%)
Decision tree	65.4
Random forest	71.2
Support vector machine	62.6
Neural network	75.00
Convolutional neural network	84.83

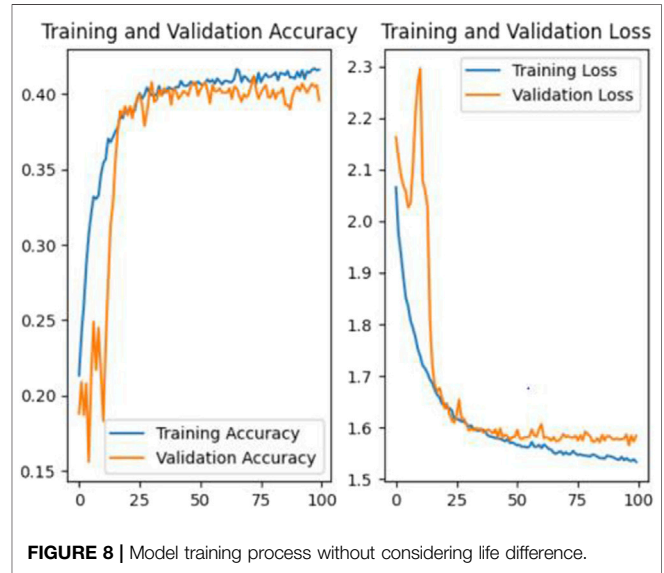
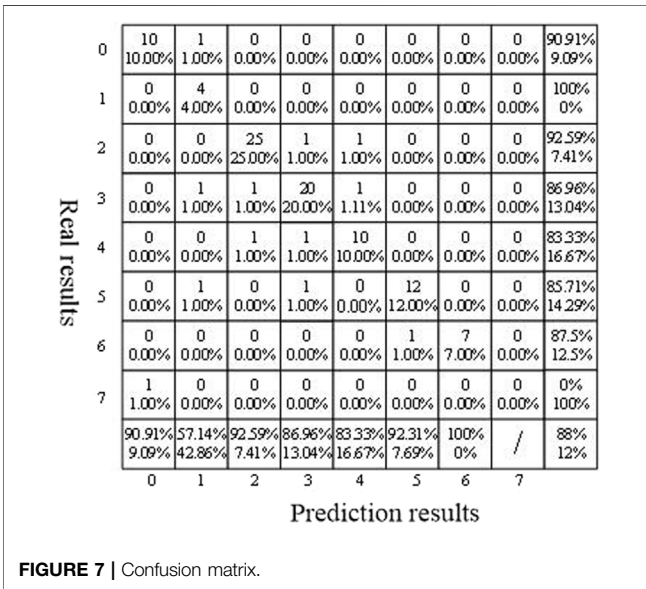


FIGURE 8 | Model training process without considering life difference.

$$d_n = \sum_m^1 p_m \times \omega_{mn} + b_n. \tag{9}$$

Similarly, the calculated results can use Relu, Tanh, and other activation functions as the output of each neuron in the whole connection layer, that is, $D_n = f(d_n)$.

The calculation process of the output layer is the same as that of the full connection layer. As shown in Eq. 9, the Softmax function is used in the activation function, and the expression is as follows:

$$\text{Softmax } f(x) = \frac{e^{x_i}}{\sum_{i=0}^n e^{x_i}}. \tag{10}$$

Life Prediction Model

The life prediction model is shown in Figure 3. First, the four characteristic quantities of voltage grade, rated capacity, manufacturer, and workplace are obtained using the Weibull distribution, and a total of 16 characteristics are used as the input layer of the model. The data output from the convolution layer is fused through the data, integrated into one-dimensional data, and sent to the fully connected neural network. The life prediction is

divided into eight intervals. 1–5 years is the first interval, and the probability of the result falling into this interval is P1. 6–10 years is the second interval, and the probability of the result falling into this interval is P2, and so on. The last interval is 35–40 years, and the probability of the result falling into this interval is P8. The activation layer of the convolutional neural network adopts the Relu function, the fully connected neural network adopts the Tanh function, and the output layer adopts the Softmax function (see Table 5 for specific parameters).

ACCURACY VERIFICATION OF LIFE PREDICTION MODEL

Verification of AI-Based Approach to the Life Prediction Model

K-fold cross-validation is adopted for the data set. That is, the data set is divided into k copies, of which k-1 is used as training data and the remaining one is used as test data. There are 501 groups of transformer data in total. A total of 100 groups were considered test data and the rest as training data. The training process is shown in Figure 4.

The prediction results of the last 100 test data are shown in Figure 5. Through TSNE visualization, the classification results of 100 data types are displayed, as shown in Figure 6.

It can be seen from **Figure 5** that most of the prediction results are consistent. Each color in **Figure 6** represents a prediction interval. It can be seen that the graphs of each interval are well distinguished. It shows that the life prediction model has high accuracy, and the life prediction confusion matrix of each classification is shown in **Figure 7**.

The accuracy is low due to the small number of training and tests in the eighth division. The prediction accuracy of other life intervals is high, which is more than 80%.

Comparison With Other Models

To verify the superiority of the model in transformer life prediction, the model is compared with the following other models.

1) Prediction results of different models

To verify the ability of the convolutional neural network in life prediction, decision tree, random forests, support vector machine, neural network, and deep confidence network were used to simulate the same data. The simulation results are shown in **Table 6**.

It can be seen from **Table 6** that a convolutional neural network has higher prediction accuracy in transformer life prediction. Compared with the current common prediction algorithms, the accuracy is improved by more than 10%.

2) Influence of life differentiation on life prediction results

To verify the impact of life differentiation on life prediction results, only the average life in the data of rated capacity, voltage level, manufacturer, and the working city was considered. Four data of k_1 , k_5 , k_9 , and k_{11} were used as the input of the convolutional neural network. The training results are shown in **Figure 8**.

According to the results, the prediction accuracy of the transformer life prediction model without considering the phenomenon of life differentiation can only reach 40.37%. Compared with the model proposed in this article, the accuracy was reduced by 52.41%. This is because more

characteristic information was extracted from the transformer life distribution data, which improved the identification of the training data and thus improved the final accuracy.

CONCLUSION

Based on the statistics of the scrapped data of transformers provided by power supply companies, this article analyzes the impact of life differentiation on the reliability evaluation of transformers. According to this phenomenon, the information containing life-differentiation information is extracted from the data and used as the input of the life prediction model based on a convolutional neural network. Compared with other prediction algorithms, the superiority of the convolutional neural network in life prediction is verified. In comparison with the life prediction model without considering the phenomenon of life differentiation, it is verified that the life prediction model considering the phenomenon of life differentiation has higher prediction accuracy.

In the future, the transformer life prediction method based on an AI approach will become the mainstream in the industry. However, it still needs to overcome the dependence on the data sample size. The data source of this article was limited, and more aging factors were not considered, which need to be further improved.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

LL—paper writing and submission; LH—data acquisition; ML—model building; ZL—data validation; and XW—proofreading.

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